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Impact of robotics on unemployment: Moderating effect of the national culture

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ABSTRACT

The integration of robotics has created significant opportunities while simultaneously introduced labour market challenges. The aim of this exploratory research is to investigate the impact of robotic adoption on unemployment in a cross-country context. By presenting a novel theoretical framework that integrates the Innovation Diffusion Theory (IDT) and the Absorptive Capacity Theory (ACT), and analysing a panel data from 33 countries, we show that countries with stronger absorptive capacity are better positioned to convert robotics adoption into employment gains. We further test whether national culture, proxied by Hofstede's cultural dimensions, moderates this relationship, uncovering a substantial heterogeneity across six cultural factors. This provides a practical blueprint for policymakers with clear evidence that uniform approaches to robotics adoption are unlikely to be effective and robotics policies must be tailored to local cultural norms, institutional capabilities, and national readiness. The policymaker should prioritise capability building alongside adjustment measures that support inclusive labour-market transitions.

1. Introduction

The world is rapidly approaching a 'fourth industrial revolution', which is changing the global manufacturing system, work, and people's lives (Acemoglu and Restrepo, 2018; De Sousa Jabbour et al., 2018; Verma and Singh, 2022). This revolution involves a confluence of various digital technologies (e.g., IoT, advanced robotics) with new materials (e.g. bio or nano-based) and processes e.g. data-driven production, artificial intelligence, synthetic biology (Koh et al., 2019). Among the new technologies, robotics dramatically improve industrial performance (Upchurch, 2018; Lloyd and Payne, 2019; Le et al., 2021; Kromann et al., 2020; Chen et al., 2023). However, the impact of robotic adoption on unemployment in a country remains inconclusive. In this paper, we ask the following question. *How does robotic adoption influence the unemployment across the sampled countries?*

Proliferating robotics adoption in the workplace can have both destructive[1] and creative effects[2] on the labour force (Acemoglu and Restrepo, 2018, 2019, 2020). Evidence shows an ambiguous impact due to robotics adoption on unemployment (Focacci, 2021), or a negative impact (Gentili et al., 2020; Leigh et al., 2019; García-Romanos and Martínez-Ros, 2024). Better understanding and empirical evidence of unemployment and economic growth will have profound implications

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[1] Destructive effect of robotic adoption is defined as the "employment decline resulting from establishments that contract or shut down." (*New Information on Job Creation and Destruction: The Economics Daily: U.S. Bureau of Labor Statistics*, 2001).

[2] Creative effect of robotic adoption is defined as follows: "the employment growth contributed by establishments that expand or start up." (*New Information on Job Creation and Destruction: The Economics Daily: U.S. Bureau of Labor Statistics*, 2001)

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for the future of work, economic policy and economic growth. To understand the differential effects of robotics adoption on unemployment across a range of countries, this study employed a theoretical framework consisting of Innovation Diffusion Theory (IDT)[3] and Absorptive Capacity Theory (ACT)[4] (Roger et al., 2022; Kim and Chakraborty, 2024). Despite the five stages of IDT being possessing knowledge, persuasion, decision, implementation, and confirmation, the five stages are not individually operationalised. The robotic adoption variable (robotic density) indicates the cumulative outcome of these stages across country-industry-year observations. This proxy captures the extent to which robotics has diffused across national contexts, consistent with IDT's conceptual framework. As country-level attributes and cultural dimensions are important factors that can affect the adoption of any technological innovation, we control and consider their moderating effect respectively (De Mooij, 2000).

Data was collected from the IFR (International Federation of Robotics), Hofstede, and the ILO (International Labour Organisation) to consider the above research question. The IFR measures the delivery of "multipurpose manipulating industrial robotics," based on the definitions of the International Organization for Standardisation (ISO), which allow us to compare robotic adoption numbers across country-industry pairs and over time. Specifically, the IFR definition refers to a "manipulating industrial robotic as defined by ISO 8373: "An automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation application" (IFR, 2023).[5] From advanced econometric analysis, we find that robotics adoption positively affects employment, which varies significantly across countries when cultural dimensions are positioned as moderators. The study's findings complement the existing literature (Jung and Lim, 2020). In practice, the research outcomes will guide policymakers to modify or develop new employment policies focusing on the rapid adoption of robotics. The significant variation in employment outcomes across countries with similar levels of robotic adoption underscores the importance of national absorptive capacity and cultural context. This supports our theoretical framework which states that diffusion alone (IDT) is insufficient without the enabling infrastructure and institutional readiness captured by ACT. Our findings suggest that countries with a stronger absorptive capacity, as reflected in their higher R&D, education, and innovation scores, are better positioned to convert robotic adoption into employment gains. To the best of our knowledge, this is the first study where the role of national culture is considered as a moderating factor in explaining the impact of robotics adoption on unemployment. We also make a novel contribution to this study by developing the theoretical framework for IDT and ACT.

The next section focuses on a critical analysis of the related literature and identifies the most relevant theoretical framework for developing the hypotheses utilised in this study. Later, we establish sections on the methodology, results, and conclusions.

[3] Innovation diffusion theory is the decision about whether to adopt an innovation that is comprised of five stages: knowledge, persuasion, decision, implementation, and confirmation (Rogers, 1983).

[4] Absorption Capacity Theory is the ability to learn from external knowledge through the processes of knowledge identification, assimilation and exploitation (Cohen and Levinthal, 1989).

[5] See also the ISO definitions at https://www.iso.org/obp/ui/#iso:std:iso:8373:ed-2:v1:en.

2. Literature review, theoretical framework and hypotheses development

Over the years, the progress in automation technology-initiated research on the direct and indirect effects of creative destruction[6] has revealed that if the rate of technological progress accelerates, the life cycle of jobs created will be shorter (Aghion and Howitt, 1994; Aghion et al., 2016). Thus, due to technological progress, the job destruction rate will increase as a direct effect of "creative destruction" (Aghion et al., 2016). The indirect effect of "creative destruction" is the corresponding reduction in payback period due to the shortening of the job life cycle caused by technological progress. This inhibits the creation of some new jobs and increases the flow of unemployment because of the reduced job openings (Aghion et al., 2016). Previous studies in different countries and industries support the destruction effect (David, 2017; Frey and Osborne, 2017; Damiani et al., 2022; Chen and Frey, 2024).

On the other hand, when researchers measured robotic adoption per thousand workers, they found that the creative effect of robotic adoption on wages is offset by employment losses in their sample (Borjas and Freeman, 2019; Compagnucci et al., 2019). Most of the recent literature supports the creative effect of robotic adoption on net employment with a marginal negative effect (Hötte et al., 2023). Moreover, we also find evidence of the insignificant effect of robotic adoption on employment in developing countries, but when compared with developed countries, they experience productivity gains by adopting robotics in various industries (Dekle, 2020; Fu et al., 2021).

Thus, there is an unresolved tension in the existing literature regarding the impact of robotics on employment. Foundational works (Aghion and Howitt, 1994; Aghion et al., 2016) establish the dual trajectory of creative destruction in labour markets. However, the extant empirical findings from recent years appear to suggest that the impact of robotics on employment across countries and stages of development remains ambiguous (e.g., Hötte et al., 2023; Dekle, 2020; Fu et al., 2021). This inconsistency highlights the need for a theoretically grounded analysis that captures both the spread of technological innovation and the socio-institutional capacity to harness it effectively (Dabić et al., 2023).

To address this, we integrate IDT and ACT not merely as citations but as complementary analytical lenses that frame our cross-country investigation. IDT (Rogers, 1962) allows us to conceptualise how robotics technologies disseminate across economies, progressing through five distinct stages, which are knowledge, persuasion, decision, implementation, and confirmation (Al-Rahmi et al., 2019) (refer to Appendix 3 for more elaborations on how the five stages of innovation diffusion are applied to explain the conflicting results in the existing literature). These stages help explain how both organisations (Vargo et al., 2020) and individuals (Kim and Chakraborty, 2024) are influenced by observable successes in advanced economies, leading to emulative adoption trends. For instance, exposure to the positive employment outcomes of robotics in high-income countries can enhance acceptance in others, especially when the dissemination is reinforced through globalised communication and technology transfer (Crescenzi and Gagliardi, 2018).

Yet the diffusion of innovation alone is not sufficient for effective utilisation. Here, ACT (Cohen and Levinthal, 1990) plays a crucial role by capturing a country's ability to identify, assimilate, and apply external knowledge. We argue that the mere availability of robotics is not predictive of employment outcomes. Rather, the national absorptive capacity shaped by factors such as R&D infrastructure, human capital, and institutional readiness (Castellacci and Natera, 2013; Wang et al.,

[6] Creative Destruction is defined as "job turnover rate," and "the sum of the job creation and job destruction rates" (Aghion et al., 2016, p. 3881). *Formula:* $\textit{Creative destruction} = \textit{net employment} = \textit{job creation} + \textit{job destruction}(\textit{negative number})$.

2020) moderates this relationship. Countries with stronger absorptive capacities are better positioned to convert adoption into positive employment outcomes, while those lacking these foundational attributes may experience marginal or even adverse effects (Lau and Lo, 2014).

By meaningfully integrating IDT and ACT, we develop a dual-theoretical foundation to explore not just whether robotics affects employment across countries, but how and why these effects vary depending on the interplay between diffusion dynamics and national absorptive capabilities. To operationalise these theories, we derive the key variables from their conceptual foundations. Robotic adoption per thousand workers serves as a proxy for innovation diffusion, capturing the extent of technology spread across countries and industries. ACT is reflected through control variables such as R&D expenditure, tertiary education enrolment, innovation index, and trade openness. These indicators represent a country's ability to identify, assimilate, and exploit external technological knowledge, aligning with ACT's core dimensions. This integrated perspective directly responds to persistent gaps in the literature and informs our hypothesis development in the context of transnational technology diffusion.

H1. Robotics adoption positively affects employment and thus reduces the unemployment rate.

The adoption of technology in every country is different because of the differences in economic conditions, infrastructure, and education (Castellacci and Natera, 2013; Jung and Lim, 2020; Leigh et al., 2019). Thus, the diffusion of innovation and absorption of such knowledge across borders will vary (Derudder and Liu, 2024). Regarding technology adoption, researchers have indicated the cultural differences among nations as another important factor to consider (Erumban and De Jong, 2006; Desmarchelier and Fang, 2016; Franque et al., 2021; Khan, 2022; Chandra et al., 2022). However, these studies do not explain the adoption of robotics and have yet to consider all possible dimensions of the national culture, as explained by Hofstede (1984, 2001)[7]. National cultures are shared value systems that reflect prevailing societal orientations, desirable goals, and aspired end-states with a lasting imprint on societies and individuals and distinguishing one society from another. (Hofstede, 2001). Thus, it becomes imperative to use national culture as a moderating factor to elucidate the transmutation of cultural disparities into the observable variations in robotic adoption on a collective, worldwide scale. Besides Hofstede's cultural dimensions, scholars have proposed other cultural dimensions (Schwartz's framework, Global leadership and organisational behaviour effectiveness, and the World Values Survey) (Steenkamp, 2001; Salehan et al., 2018). However, Hofstede's framework is one of the most widely used frameworks to investigate national variance between countries in social science until recent days, and so we adopted it in our study (Salehan et al., 2018; Abbasi et al., 2021).

Power Distance (PDI) indicates the inequality of power distribution in a society, reflected in the practices of different organisations in that country (Naumov and Puffer, 2000). Countries with a high PDI tend to have firms that are less innovative than low PDI countries (Bukowski and Rudnicki, 2019). If innovation is related to a particular technology, high PDI plays a positive role (Malik et al., 2021). As innovation does not always mean technological innovation, based on the above argument, we expect a country with a prominent high-power distance to have a positive impact on the positive relationship between robotic adoption and employment.

Under the Individualism/Collectivism (IDV) dimension, individuals either prefer to focus mainly on themselves to make decisions or become integrated into strong, cohesive communities (Hofstede et al., 2010). Individualist-dominated societies could lead to the free expression of interest toward innovation (Griffith and Rubera, 2014). It is hard for an individualistic society to adopt technology on a wide scale because of the limited capability of individuals. Conversely, collectivism-prominent cultures apply society-wide efforts to develop scientific and technological solutions to national problems (Taylor and Wilson, 2012). However, it takes time to diffuse the knowledge of technology to be absorbed by a society that is defined as collectivism focused. Thus, we expect both individualism and collectivism to moderate the relationship between robotic adoption and unemployment positively.

As per the Masculinity (MAS) dimension, a masculine culture prioritises competition, ambition, and material success, while feminine values of solidarity, equality, and social relationships as a risk-averse (Hofstede, 2001). In a masculine culture, individuals focus on performance-based rewards (Hofstede, 2001). Thus, there is a high possibility of the absorption of technology in a high masculine culture, especially when the diffusion of technology is progressing rapidly in society.

In an Uncertainty Avoidance (UAI) society, people feel uncomfortable with uncertainty and ambiguity (Hofstede, 1984). Variations in national risk-taking capacities and innovation evaluations contribute to the differential rates of technological diffusion, suggesting that countries with higher uncertainty avoidance tend to be more risk-averse and resistant to change (Freeman, 1990). Thus, there is a higher probability that a low UAI country will strengthen the negative relationship between robotic adoption and unemployment.

Long-term goal-oriented cultures turn their attention to the future at the expense of the present, while short-term cultures turn their attention to the present at the expense of the future (Hofstede et al., 2010). As knowledge diffusion and later technology absorption by any society takes time (Malik et al., 2021), a long-term goal-orientation culture is more likely to be a positive moderator.

Cultures leaning toward restraint often views life as challenging, emphasising duty and moral discipline over freedom. Conversely, indulgent cultures are marked by optimism, personal control, impulsiveness, and the value placed on friendships and freedom of speech (Jaiswal and Zane, 2022). Societies with fewer constraints on creativity are potentially conducive to exploration and innovation. Thus, high indulgence could strengthen the positive relationship between robotic adoption and employment.

Although we can use IDT to capture the characteristics of a country as part of explaining the intention of adopting technology, it alone cannot explain the absorptive capacity of said technology in a multi-country set-up (Castellacci and Natera, 2013). There is a chance of there to be a creation or destruction effect of adopting robotics in labour demand (Filippi et al., 2023). It is easier to conclude the relationship between robotics adoption and employment creation/destruction by considering the complementary effect of IDT and ACT in different cultural dimensions. The theoretical framework of the study is explained in Fig. 1.

Based on the above argument, we propose the following hypothesis.

H2. National cultural dimensions moderate (strengthen) the negative relationship between robotics adoption and unemployment.

3. Methodology

3.1. Sample

To examine the impact of robotic adoption on unemployment, the sample covers 33 countries from 2010 to 2019.[8] Because of COVID-19, the regulatory bodies in different countries were disrupted in their operation (Justy et al., 2023). To maintain the reliability of the data, we restricted the sample period to 2019. Following the literature, the data

[7] Definition and characteristics of the cultural dimensions are summarised in Table 1

[8] The panel data is strongly balance.

Table 1
Definitions and characteristics of low/high scores on the Hofstede cultural dimensions.

	Definition	Low scores on dimension	High scores on dimension
PDI (power distance index)	Degree to which large differentials of power and inequality are accepted as normal by the individual. Power distance will condition the extent to which the employee accepts that his/her superiors have more power.	Lower power distance countries have more decentralised authority and with more participatory management.	More centralised authority with levels of hierarchy and supervision characterises higher power distance countries.
IDV (individualism/ collectivism)	Degree to which the individual emphasises his/ her own needs as opposed to the group needs and prefer to act as an individual rather than as a member of a group.	In a low individualism (i.e. high collectivism) country, people are considered members of the family, and their interests are more closely aligned.	People in a society consider their own interests without taking the interests of the society as a whole into account.
MAS (masculinity/ femininity)	Represents a preference for achievement, assertiveness, control, and power.	Countries espouse feminine values tend to emphasise personal goals such as a friendly atmosphere, comfortable work environment, quality of life and warm personal relationships.	In high masculine countries, managers strive for achievement and recognition.
UAI (uncertainty avoidance index)	Uncertainty avoidance is the level of risk accepted by the individual which represents a society's tolerance for uncertainty and ambiguity.	Individuals in low uncertainty avoidance countries tend to be more flexible and have higher tolerances for differing opinions	High uncertainty avoidance countries tend to have stricter rules and laws and individuals value precision and punctuality.
LTO (long-term/ short-term orientation)	The degree to which society does or does not embrace long-term devotion to traditional values.	Values in a society with short-term orientation are related to the traits of spending extravagantly and to using available resources instantaneously for quick results.	High scores are likely to indicate that thrift and persistence are rewarded, and that social behaviour is oriented toward future rewards.
IVR (indulgence versus restraint)	This dimension represents a trade-off between indulgence and restraint.	In a restrained culture, individuals feel that life is hard and duty rather than freedom is more normal. Stricter moral discipline.	In an indulgent culture, individuals are more optimistic and feel that they have more control over their lives and are more impulsive. Friends are important and freedom of speech is common.

Source: Hofstede, 1984, 2001; Hofstede et al., 2010; The 6 Dimensions Model of National Culture by *Geert Hofstede*, 2021).

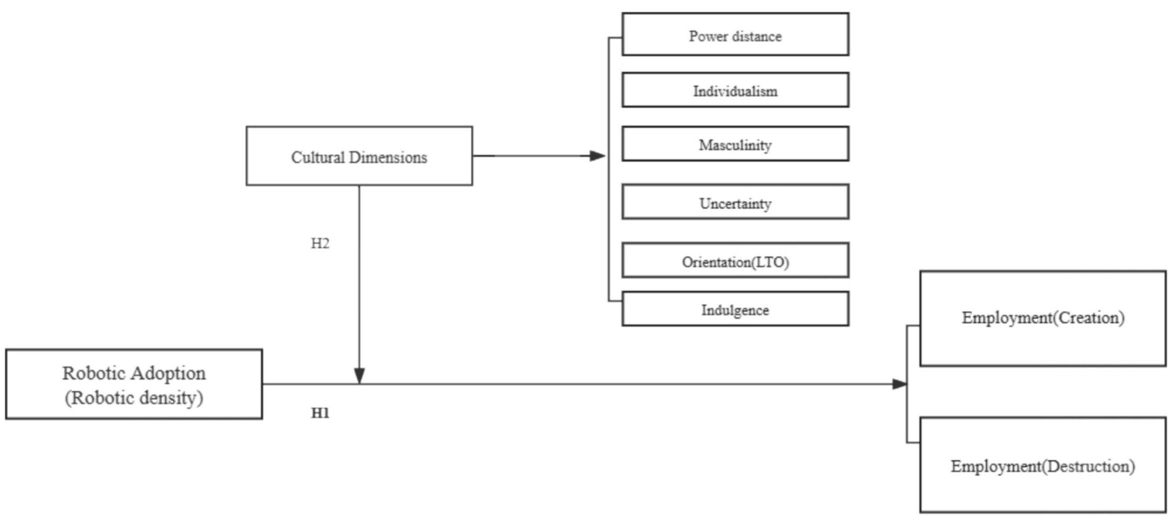

Fig. 1. Theoretical framework.

sources are as follows: the main independent variable, industrial robotic stock data from IFR (Borjas and Freeman, 2019), the dependent variable, country-level employment data, GDP per capita and the trade balance from the World Bank, Research and Development expenditure from the United Nations, average worked hours from the ILO, Innovation index from WIPO, and Education from UNESCO (Koch et al., 2021; Fu et al., 2021; Graetz and Michaels, 2018; Klenert et al., 2022). This is in addition to the group grievance index (GGI) from Fund for Peace. Among these, industry-level data on working hours was used as a control variable to address the impact of industry heterogeneity.

As the IFR and ILO industry classification standards are not identical, to ensure rigour, in this paper, we primarily adopted the IFR industry classification and merged some of the industries in the ILO to obtain six industries: agriculture; forestry and fishing; manufacturing; electricity; gas and water production and supply (referred to as electrical water production and supply); quarrying and mining; education, research and development; construction. Utilising data from the above six industries, we constructed a three-dimensional data set of country-industry-year. We obtained 1980 observations from the data on country-industry pairs over 10 years, including 33 countries and six industries.

3.2. Variable description

In Appendix 1, we provide details of all variables used in this study. Following the prior literature, we divide the total stock of industrial robotics[9] by the number of employed people per thousand to define the independent variable Robotic adoption ($Robotic_{it}$) (Gentili et al., 2020;

[9] In this research, the explanatory variables only include industrial robotics defined as: "An automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation application" (IFR, 2023).

Klenert et al., 2022, p. 285).[10] The robotic adoption variable (Robotic density) is conceptually grunded in IDT, representing the cumulative diffusion of robotics across national contexts. Similarly, absorptive capacity is operationalised through control variables including R&D expenditure, education, innovation index, and trade openness. These variables are derived from ACT and capture the institutional and infrastructural readiness of a country to translate technological adoption into employment outcomes.

$$X_{it} = \frac{Robotics_{it}}{Labour_{it}} = Robotic\ Density \tag{1}$$

3.3. Variable selection

The dependent variable is unemployment rate which is defined as the share of the labour force without work but available for and actively seeking employment. Importantly, "job destruction" does not necessarily imply that jobs permanently disappear (Focacci, 2021). With technological adoption (robotics in this case), tasks may be completed more quickly or re-organised rather than eliminated, and often reassign workers across the processes (Dekle, 2020). Consequently, the employment effect is an empirical question, and this study used unemployment as a tractable macro indicator of labour-market slack. Unemployment is among the most widely used macroeconomic indicator for characterising and forecasting labour-market conditions (Jo et al., 2023). Unemployment rate excludes inactive working-age individuals who are not seeking work or are unavailable to start (e.g., full-time students aged 15 to 24), which can reduce the measurement error (Naccarato et al., 2017).

Discouraged workers who cease searching in weak labour markets are not counted as unemployed, which can mechanically lower the recorded unemployment without any underlying improvement in slack (Lee and Parasnis, 2014). The cross-national data drawn from World Bank compilations widely used in academic research facilitates coverage, but differences in survey design, recall periods, and the treatment of informal work can compromise cross-country comparability (Jung and Lim, 2020). To enhance robustness, this research therefore estimates by adding the labour-force participation rate (LFPR) as an alternative outcome. Consistent results and significance across the outcomes increase the confidence that our conclusions are not driven by the limitations of the unemployment measure.

Following Strese et al. (2016), we model the cultural dimensions as moderators via interaction terms (see Appendix 2) and include a comprehensive set of control variables.

3.4. Descriptive statistics

In Table 2, the mean robotic adoption is 1.382, with a standard deviation of 1.738. This implies a variation in the adoption of robotics across the sample countries and is consistent with Gentili et al. (2020). Differences between the minimum value of zero and the maximum of 11.9 support the arguments of the IDT and ACT. Multicollinearity can occur when one variable can be used to predict the other significantly. This issue impacts the standard errors of the individual coefficient values that can lead to Type I or Type II errors of hypothesis testing. We adopt Variance Inflation Factor (VIF) to assess the multicollinearity of the explanatory variables. Our test of VIF is presented in Table 2 and it shows that the VIF value for each explanatory variable is below the recommended threshold of 10 (Hair Jnr et al., 2010). Hence, there are no problems with multicollinearity.

We report the summary statistics of country-wise unemployment and robotic adoption in Tables 3 and 4, respectively, which are consistent with the literature (Dekle, 2020; Gentili et al., 2020; Leigh et al., 2019). South Korea, Japan, and Germany, which have the highest robotic densities, also come out on top in employment. In contrast, Latvia, Croatia, and Bulgaria, which have the lowest robotic densities, lag

Table 2
Descriptive statistics.

Variable	Obs	Mean	Std. dev.	Min	Max	VIF
Unemployment	1980	8.268	4.788	0.250	27.690	
Robotic adoption	1980	1.382	1.738	0.000	11.900	3.577
R&D	1980	4.135	9.787	0.005	67.778	2.477
Education	1980	4.211	0.283	3.230	4.959	1.914
Average workhr	1980	3.681	0.123	3.268	6.075	1.128
Trade	1980	5.218	1.393	2.585	8.049	3.274
Population	1980	87.239	237.004	0.410	1407.750	4.019
GDP	1980	10.007	0.674	8.423	11.084	7.320
Innovation	1980	47.235	8.865	28.100	64.800	4.985
Power distance	1980	55.485	19.865	11	104	2.528
Individualism	1980	52.758	21.126	18	91	4.384
Masculinity	1980	48.242	24.615	5	110	1.812
Uncertainty avoidance	1980	72.424	21.959	23	112	2.255
Orientation(lto)	1980	56.438	20.565	20.403	100	2.763
Indulgence	1980	45.380	20.447	12.946	97.321	3.058

Notes: Dependent variable: Unemployment; Independent variable Robotic adoption. Control variables: Logarithm of Trade (trade); Logarithm of GDP per capita, current U.S. dollars (GDP); Logarithm of average worked hours (Average workhr); Innovation Index (inn); Population by Country (Population); Logarithm of Tertiary school enrolment (Education); Research and development investment (U.S. trillion dollars) (R&D). Cultural dimensions: Individualism/collectivism (Individualism), Uncertainty avoidance index (Uncertainty avoidance) dimensions, Power distance (PDI), Masculinity/femininity (Masculinity), Long-term/short-term orientation (orientation), Indulgence versus restraint (Indulgence).

Table 3
Descriptive statistics country-wise unemployment.

Country	Mean/prop.	Freq.	SD	Min.	Max.	Median
Argentina	7.956	60	0.895	7.100	9.840	7.645
Austria	5.238	60	0.499	4.560	6.060	5.150
Belgium	7.463	60	1.051	5.360	8.520	7.685
Brazil	9.427	60	2.328	6.760	12.790	8.485
Bulgaria	9.048	60	2.958	4.230	12.940	9.710
China	4.544	60	0.092	4.310	4.650	4.560
Croatia	13.131	60	3.525	6.620	17.290	13.390
Denmark	6.588	60	1.037	5.020	7.800	6.605
Estonia	8.357	60	3.602	4.450	16.710	7.055
Finland	8.160	60	0.756	6.690	9.380	8.290
France	9.578	60	0.588	8.410	10.350	9.625
Germany	4.739	60	1.134	3.140	6.970	4.800
Greece	21.594	60	4.586	12.720	27.690	22.460
Hungary	7.432	60	3.087	3.420	11.170	7.270
Italy	10.756	60	1.433	8.360	12.680	10.930
Japan	3.580	60	0.881	2.350	5.100	3.490
Latvia	11.541	60	3.990	6.310	19.480	10.360
Lithuania	10.549	60	3.836	6.150	17.810	9.910
Malta	5.261	60	1.140	3.620	6.850	5.550
Mexico	4.341	60	0.743	3.270	5.300	4.560
Netherlands	5.538	60	1.322	3.380	7.420	5.405
Poland	7.436	60	2.586	3.280	10.330	8.245
Portugal	11.491	60	3.184	6.460	16.190	11.760
Romania	6.057	60	1.202	3.910	7.180	6.795
Slovakia	10.937	60	3.115	5.760	14.390	11.515
Slovenia	7.737	60	1.807	4.450	10.140	8.110
South Korea	3.337	60	0.385	2.750	3.820	3.435
Spain	20.484	60	3.890	14.100	26.090	20.625
Sweden	7.472	60	0.689	6.360	8.610	7.615
Thailand	0.630	60	0.157	0.250	0.830	0.640
Turkey	10.268	60	1.492	8.150	13.670	10.450
USA	6.227	60	2.064	3.670	9.630	5.725
United Kingdom	5.952	60	1.657	3.740	8.040	5.705

[10] We follow the definition of robotic as defined by the International Organization for Standardisation (ISO). See also the ISO definitions at https://www.iso.org/obp/ui/#iso:std:iso:8373:ed-2:v1:en.

Table 4
Descriptive statistics country-wise robotics adoption.

Country	Mean/prop.	Freq.	SD	Min.	Max.	Median
Argentina	0.156	60	0.054	0.069	0.254	0.151
Austria	1.977	60	0.444	1.430	2.757	1.826
Belgium	1.753	60	0.240	1.384	2.092	1.763
Brazil	0.112	60	0.032	0.062	0.163	0.110
Bulgaria	0.085	60	0.048	0.027	0.173	0.074
China	0.402	60	0.327	0.067	1.037	0.280
Croatia	0.082	60	0.035	0.030	0.142	0.082
Denmark	1.987	60	0.274	1.591	2.371	1.968
Estonia	0.183	60	0.117	0.063	0.427	0.143
Finland	1.776	60	0.058	1.692	1.884	1.774
France	1.321	60	0.096	1.217	1.550	1.311
Germany	4.506	60	0.430	3.902	5.226	4.475
Greece	0.122	60	0.042	0.066	0.188	0.118
Hungary	1.196	60	0.523	0.377	2.042	1.093
Italy	2.798	60	0.156	2.662	3.186	2.741
Japan	4.832	60	0.251	4.492	5.315	4.835
Latvia	0.029	60	0.023	0.008	0.079	0.023
Lithuania	0.092	60	0.087	0.010	0.279	0.056
Malta	0.186	60	0.174	0.030	0.441	0.074
Mexico	0.298	60	0.236	0.000	0.683	0.243
Netherlands	1.121	60	0.331	0.656	1.600	1.100
Poland	0.509	60	0.243	0.215	0.958	0.455
Portugal	0.747	60	0.229	0.466	1.144	0.666
Romania	0.225	60	0.141	0.036	0.467	0.179
Slovakia	1.919	60	0.861	0.807	3.223	1.705
Slovenia	2.309	60	0.919	1.070	4.013	2.130
South Korea	7.812	60	2.584	4.174	11.900	7.382
Spain	1.679	60	0.092	1.542	1.856	1.652
Sweden	2.380	60	0.254	2.075	2.741	2.351
Thailand	0.617	60	0.214	0.253	0.903	0.660
Turkey	0.289	60	0.144	0.096	0.535	0.270
USA	1.545	60	0.217	1.245	1.902	1.537
United Kingdom	0.557	60	0.065	0.464	0.663	0.556

behind in terms of employment. We found there to be a very low and similar unemployment rate in countries with high robotic adoption, consistent with expectations under Hypothesis 1. Accordingly, robotic adoption might also offset job loss by creating new jobs.

In Table 5, the Pearson correlation coefficients between unemployment and robotic adoption are significantly positive. The correlation between other variables does not show as significantly high.

4. Results and discussion

4.1. Identification strategy

Our identification strategy is grounded in the theoretical frameworks of IDT and ACT, both of which inform our modelling approach. IDT conceptualises technology adoption as a staged process that unfolds over time supporting our inclusion of time dummies to capture the temporal dimension of robotics diffusion (Denicolai et al., 2016; Caporale et al., 2018). This aligns with the premise that adoption and its effects are not immediate but shaped by progressive exposure and assimilation. In parallel, ACT emphasises that the benefits of innovation depend on the institutional and sectoral capacity to absorb external knowledge. Accordingly, we adopt pooled OLS with industry and year fixed effects in a model to address the systematic differences in industry and year. In addition, the industry fixed effect is used due to industry-specific unobserved heterogeneity, recognising that robotics adoption may vary across sectors and it can be randomly correlated with the error terms (Chaney et al., 2021). Since the culture dimensions do not vary across industry and time, we cannot use fixed effect panel regression. However, we also conducted the random effects panel regression in our base line analysis. Finally, we applied the Breusch–Pagan Lagrange Multiplier test to confirm the absence of residual heterogeneity. Collectively, these empirical choices reflect the dynamic, context-sensitive nature of robotics diffusion and absorption, in line with both IDT and ACT.

The baseline model of this study is given below:

$$Unemployment_{it} = \beta_0 + \beta_1 ln\ Robotic_{it} + Controls_{ijt} + \gamma_{jt} + \varepsilon_{ijt} \quad (2)$$

where i refers to the country, j industry, t year. γ_{jt} denotes industry and year dummy, and ε_{ijt} is the random error term.

4.2. Empirical findings

In the first model in Table 6, there is a negative and significant impact due to robotic adoption on unemployment. To mitigate concerns regarding the possibility of overfitting, this research progressively incorporates non-essential control variables, including trade, population, and GDP per capita.[11] The following five models show similar results, where we add the control variables and cultural dimensions. Differing from ambiguous results (Focacci, 2021), our findings support Hypothesis 1 and align with recent trends in the literature that propose new employment opportunities with the adoption of robotics (Dekle, 2020; Gentili et al., 2020).

As discussed in the theoretical framework section, innovation diffusion depends on several country-level factors (Castellacci and Natera, 2013). Higher international trade indicates higher economic growth and employment opportunities, meaning a lower unemployment rate (Ma et al., 2015). Thus, we found there to be a negative and significant coefficient for international trade. Moreover, there is a positive and significant relationship between total population, GDP, and education, even when we observe a significant negative relationship between robotic adoption and unemployment. Based on the theoretical framework, we argue that the increasing population over the years means it takes more time to complete the technology adoption life cycle (Coccia, 2014). With the development of the economy, the need for skilled and educated labour will also increase. Still, the expansion of education is not compatible with the evolving skill structure desired by enterprises (O'Reilly et al., 2015). These variables will need longer to show a negative relationship with unemployment. However, the significant negative coefficients for R&D expenditures and the innovation index imply that a country's technological absorptive capacity enhances its competitiveness and the sustainability of the labour market (Bogliacino and Vivarelli, 2012; Persaud and Zare, 2023). The findings of Model 5 justify the suitability of the adoption of the IDT in our research. In addition, the change in the coefficient value in Model 5 and Model 6 provides evidence of the absorption of robotics in different cultures. It supports the need for the IDT and ACT to discuss new technology adoption (Gkypali et al., 2018). The results also support H1 and extend the literature on robotic adoption and unemployment (Leigh et al., 2019). The gradual increase of the R-squared shows the fit of the models. The variables are incorporated into the empirical model in an incremental manner. The initial analysis is conducted using only the

[11] Guardrails against overfitting and multiple comparisons. We assessed the joint relevance of the macro control block: trade, population, and GDP per capita. Using a Wald test to assess the null hypothesis showed that the coefficients are jointly zero. The test rejects decisively, $F(3, 1951) = 79.56$, $p < 0.001$, indicating substantial explanatory power for recorded unemployment. As a parsimony check, we trim non-essential controls (dropping, in turn, one block at a time) and re-estimate the baseline; across these specifications, the signs of the coefficients of interest and the magnitudes of the average marginal effects remain stable, with the confidence intervals largely overlapping those in the main tables. To address multiple testing in the six interaction models (the culture × robots terms considered as a single family), we implement the Romano–Wolf step-down adjustment (bootstrap-based, finite-sample consistent for strong dependence). Using 5000 resamples, the step-down familywise error rate (FWER)-controlled p-values retain significance for the primary moderators (PDI, IDV, MAS, UAI, LTO, IVR), leaving all qualitative conclusions unchanged. The results are materially similar under Holm–Bonferroni and BH–FDR adjustments.

Table 5
Correlation matrix.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) Unemployment	1.000														
(2) Robotic adoption	−0.283	1.000													
	(0.000)														
(3) Education	0.350	0.213	1.000												
	(0.000)	(0.000)													
(4) R&D	−0.218	0.216	0.041	1.000											
	(0.000)	(0.000)	(0.067)												
(5) Innovation	−0.274	0.464	0.216	0.368	1.000										
	(0.000)	(0.000)	(0.000)	(0.000)											
(6) Trade	−0.297	0.417	−0.110	0.610	0.371	1.000									
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)										
(7) GDP	−0.054	0.486	0.396	0.265	0.797	0.343	1.000								
	(0.017)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)									
(8) Population	−0.182	−0.065	−0.344	0.513	0.043	0.466	−0.258	1.000							
	(0.000)	(0.004)	(0.000)	(0.000)	(0.053)	(0.000)	(0.000)								
(9) Average workhr	−0.130	−0.050	−0.105	0.131	−0.085	0.123	−0.191	0.245	1.000						
	(0.000)	(0.027)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)							
(10) Power distance	0.112	−0.173	−0.404	−0.100	−0.589	−0.080	−0.627	0.217	0.128	1.000					
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)						
(11) Individualism	−0.009	0.004	0.169	0.223	0.555	0.204	0.660	−0.233	−0.147	−0.595	1.000				
	(0.692)	(0.863)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
(12) Masculinity	−0.084	0.159	−0.304	0.253	−0.159	0.366	−0.062	0.203	0.067	0.279	0.027	1.000			
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.000)	(0.003)	(0.000)	(0.225)				
(13) Uncertainty avoidance	0.289	−0.024	0.113	−0.300	−0.503	−0.274	−0.259	−0.356	−0.080	0.399	−0.403	0.162	1.000		
	(0.000)	(0.293)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
(14) Orientation(lto)	−0.099	0.445	0.013	0.015	0.248	0.077	0.106	0.186	−0.025	0.046	0.010	0.129	−0.088	1.000	
	(0.000)	(0.000)	(0.555)	(0.498)	(0.000)	(0.001)	(0.000)	(0.000)	(0.267)	(0.041)	(0.646)	(0.000)	(0.000)		
(15) Indulgence	−0.189	0.002	−0.063	0.122	0.290	0.343	0.422	−0.089	0.036	−0.302	0.251	−0.003	−0.193	−0.532	1.000
	(0.000)	(0.922)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.111)	(0.000)	(0.000)	(0.894)	(0.000)	(0.000)	

Notes: Dependent variable: Unemployment; Independent variable Robotic adoption. Control variables: Logarithm of Trade (trade); Logarithm of GDP per capita, current U.S. dollars (GDP); Logarithm of average worked hours (Average workhr); Innovation Index (inn); Population by Country (Population); Logarithm of Tertiary school enrolment (Education); Research and development investment (U.S. trillion dollars) (R&D). Cultural dimensions: Individualism/collectivism (Individualism), Uncertainty avoidance index (Uncertainty avoidance) dimensions, Power distance (PDI), Masculinity/femininity (Masculinity), Long-term/short-term orientation (orientation), Indulgence versus restraint (Indulgence).

Table 6
Baseline regression.

Variables	Unemployment							Labour force participation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Robotic adoption	−0.687***	−0.599***	−0.611***	−0.565***	−0.571***	−0.516***	−0.338***	0.266***
	(−15.02)	(−14.57)	(−13.87)	(−12.89)	(−12.51)	(−6.76)	(−48.41)	(4.43)
R&D		−0.030***	−0.034***	−0.052***	−0.062***	−0.114***	−0.002	0.087***
		(−6.39)	(−4.54)	(−6.90)	(−8.10)	(−11.47)	(−0.91)	(9.19)
Education		8.053***	8.103***	8.532***	7.448***	8.431***	2.580***	−4.146***
		(22.55)	(20.85)	(20.72)	(19.3)	(19.72)	(378.6)	(−12.16)
Average workhr		−6.230***	−6.276***	−6.902***	−5.203***	−4.078***	−0.384	−1.667**
		(−3.13)	(−3.11)	(−3.45)	(−3.19)	(−3.10)	(−0.43)	(−2.23)
Trade			0.049*	−0.036	−0.401***	−0.406***	−1.513***	0.216**
			−0.6	(−0.44)	(−4.34)	(−4.14)	(−215.49)	(2.09)
Population				0.002***	0.005***	0.007***	0.004***	−0.001
				(7.01)	(10.99)	(12.43)	(368.37)	(−1.42)
GDP					2.960***	3.386***	−3.393***	−2.210***
					(9.85)	(11.42)	(−212.35)	(−6.29)
Innovation		−0.138***	−0.138***	−0.136***	−0.287***	−0.188***	−0.045***	0.136***
		(−13.08)	(−12.72)	(−12.58)	(−14.98)	(−9.29)	(−549.48)	(5.85)
Power distance						0.074***	−0.007***	−0.063***
						(16.17)	(−29.97)	(−13.64)
Individualism						0.041***	0.117***	−0.093***
						(5.93)	−129.32	(−14.33)
Masculinity						0.005	−0.004***	−0.043***
						(1.52)	(−72.03)	(−13.73)
Uncertainty avoidance						0.018***	0.072***	−0.117***
						(4.75)	(149.67)	(−19.97)
Orientation(lto)						−0.032***	0.041***	0.017***
						(−5.11)	(88.4)	(3.20)
Indulgence						−0.039***	0.055***	0.064***
						(−5.74)	(92.34)	(10.09)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	–	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	–	Yes
Constant	9.968***	5.69	5.459	6.177	−16.815**	−37.927***	27.242***	111.872***
	(26.14)	(−0.73)	(−0.7)	(−0.8)	(−2.36)	(−6.14)	(7.87)	(29.31)
Observations	1980	1980	1980	1980	1980	1980	1980	1980
R-squared	0.125	0.403	0.403	0.408	0.44	0.51	0.142	0.644

Notes: Pooled OLS with industry and year fixed effect (Column1–6) and random effects panel regression (Column 7) are used. The dependent variable is Unemployment.; Independent variable is Robotic adoption. Control variables are Logarithm of Trade (trade); Logarithm of GDP per capita, current U.S. dollars (GDP); Logarithm of average worked hours (Average workhr); Innovation Index (inn); Population by Country (Population); Logarithm of Tertiary school enrolment (Education); Research and development investment (U.S. trillion dollars) (R&D). The moderator variables (cultural dimensions): Individualism/collectivism (Individualism), Uncertainty avoidance index (Uncertainty avoidance) dimensions, Power distance (PDI), Masculinity/femininity (Masculinity), Long-term/short-term orientation (orientation), Indulgence versus restraint (Indulgence). t-Statistics are based on robust standard errors and shown in parentheses.

*** 1% significance level.

** 5% significance level.

* 10% significance level.

core variables, yielding an R-squared value of 0.125. Subsequently, we added the control variables in Model 5, which resulted in an enhancement of the R-squared value to 0.44. Following the incorporation of the cultural dimension in Model 6, the R-squared value increased to 0.51. In other words, the impact of cultural dimensions resulted in a notable enhancement of the R-squared value, which increased from 0.44 to 0.51. As the R-squared value gradually increases, starting from Model 1 which includes no control variables, the coefficient for the impact of robotics on unemployment decreases progressively from −0.687 to −0.516 in Model 6. This explains the necessity of incorporating IDT and ACT alongside the corresponding control variables.

As the labour participation rate indicator is inversely related to the unemployment rate, the coefficient for Model 8 is positive, and the results support Model 7.

This finding aligns with the research in the field of robotics (Jung and Yang, 2025). The findings demonstrate that the explanatory capacity of the model is improved by a gradual enhancement, thereby underscoring the significance of incorporating cultural dimensions.

4.3. *Endogeneity*

To address the potential endogeneity arising from the model specification, this study adopts an instrumental-variables approach. Social cohesion is empirically linked to technology adoption (Al-Emran, 2023), and the group grievance index (GGI) captures social cohesion. The group grievance index can avoid endogeneity, and accordingly the instrumental variable satisfies the exogeneity condition. This paper follows Brzozowski and Siwińska-Gorzelak (2024) to employ a combination of under-identification, weak identification, and overidentifying restrictions tests to ensure the efficacy of the estimators. Then, regression estimation is performed leveraging 2SLS, and the results are shown in Table 7. The results in Table 7 significantly support the results of Table 6, which are in line with the expectations.

4.4. *Heterogeneity*

Developing and developed economies have different characteristics. In order to address heterogeneity, a comparison between two groups is able to provide a more robust analysis (Fu et al., 2021). Table 8 presents the empirical findings concerning the impact of robotic adoption on unemployment. A comparative analysis of the impact of robotic adoption on developed and developing countries reveals that the two groups exhibit similar trends. Nevertheless, the adoption of robotics is more effective at reducing unemployment in developing countries. The comparatively lower per capita income levels in developing countries are conducive to the more significant productivity gains that result from

Table 7
Addressing endogeneity.

Variable	Stage I	Stage II
	Group grievance index	Unemployment
IV	−0.230***	
	(−14.63)	
Robotic adoption	0.020***	−0.105***
	−6.48*	(−7.96)
R&D	−0.196**	8.271***
	(−2.03)	−21.13
Education	0.628***	−3.871***
	−3.07	(−4.74)
Average workhr	0.651***	−0.114
	−28.5	(−0.65)
Trade	−0.004***	0.005***
	(−26.23)	−4
Population	0.767***	3.989***
	−9.42	−9.09
GDP	0.023***	−0.168***
	−4.54	(−7.39)
Innovation	−0.009***	0.068***
	(−5.70)	−10.06
Power distance	−0.052***	0.011
	(−34.12)	−0.69
Individualism	0.009***	0.011**
	−8.85	−2.15
Masculinity	−0.010***	0.015***
	(−7.33)	−2.63
Uncertainty avoidance	0.029***	−0.019**
	−19.26	(−2.12)
Orientation(lto)	−0.014***	−0.047***
	(−8.40)	(−6.03)
Indulgence		−1.037***
		(−3.82)
Industry	Yes	Yes
Year	Yes	Yes
Constant	−8.606***	−44.173***
	(−8.21)	(−8.48)
KP LM statistic		204.06
KP LM p-val		0.00
KP Wald F		214.16
Observations	1980	1980

Notes: This is 2SLS regression with industry and year fixed effects. The dependent variable is unemployment.; Independent variable is Robotic adoption. Instrumental variable is Group grievance index. The Group Grievance Indicator focuses on divisions and schisms between different groups in society – particularly divisions based on social or political characteristics – and their role in access to services or resources, and inclusion in the political process. The higher the value of the indicator, the higher the division of the societal groups in the country. Control variables are Logarithm of Trade (trade); Logarithm of GDP per capita, current U.S. dollars (GDP); Logarithm of average worked hours (Average workhr); Innovation Index (inn); Population by Country (Population); Logarithm of Tertiary school enrolment (Education); Research and development investment (U.S. trillion dollars) (R&D). The moderator variables (cultural dimensions): Individualism/collectivism (Individualism), Uncertainty avoidance index (Uncertainty avoidance) dimensions, Power distance (PDI), Masculinity/femininity (Masculinity), Long-term/short-term orientation (orientation), Indulgence versus restraint (Indulgence). t-Statistics are based on robust standard errors and shown in parentheses.
*** 1% significance level.
** 5% significance level.
* 10% significance level.

Table 8
Impact of robotic adoption with country heterogeneity.

Variable	(Developed countries)	(Developing countries)
	Unemployment	
Robotic adoption	−0.455***	−4.340***
	(−5.87)	(−7.53)
R&D	−0.291***	0.076
	(−6.31)	(1.01)
Education	8.521***	0.601*
	(15.12)	(1.84)
Average workhr	−4.682***	−0.043
	(−4.52)	(−0.28)
Trade	−0.146	−8.755***
	(−1.10)	(−18.09)
Population	0.038***	0.033
	(5.05)	(1.48)
GDP	1.248***	−0.421
	(3.44)	(−0.88)
Innovation	−0.226***	0.020
	(−8.31)	(1.03)
Power distance	0.060***	−0.277***
	(13.78)	(−5.82)
Individualism	0.014*	−0.442***
	(1.87)	(−8.28)
Masculinity	−0.002	−0.559**
	(−0.47)	(−1.97)
Uncertainty avoidance	−0.004	0.573**
	(−1.10)	(2.10)
Orientation(lto)	−0.046***	0.540***
	(−7.18)	(3.15)
Indulgence	−0.012	0.545***
	(−1.37)	(12.32)
Industry fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Constant	−10.280*	15.029
	(−1.96)	(1.51)
Observations	1560	420
R-squared	0.566	0.972

Notes: Pooled OLS with industry and year fixed effects is used. The dependent variable is unemployment; Independent variable is Robotic adoption. Control variables are Logarithm of Trade (trade); Logarithm of GDP per capita, current U.S. dollars (GDP); Logarithm of average worked hours (Average workhr); Innovation Index (inn); Population by Country (Population); Logarithm of Tertiary school enrolment (Education); Research and development investment (U.S. trillion dollars) (R&D). The moderator variables (cultural dimensions): Individualism/collectivism (Individualism), Uncertainty avoidance index (Uncertainty avoidance) dimensions, Power distance (PDI), Masculinity/femininity (Masculinity), Long-term/short-term orientation (orientation), Indulgence versus restraint (Indulgence). t-Statistics are based on robust standard errors and shown in parentheses.
*** 1% significance level.
** 5% significance level.
* 10% significance level.

robotic adoption. These gains in turn engender new employment opportunities and serve to reduce unemployment rates.

4.5. Moderation effects

To examine Hypothesis 2, we introduce the moderating effect of the six cultural dimensions proposed by Hofstede (Hofstede, 1984, 2011). National culture could determine how a nation diffuses knowledge and absorbs it in its economic activity (Crescenzi and Gagliardi, 2018). In most of the literature, we find evidence of the prominence of one type of cultural dimension in a country that dominates its economic growth-related activities (Desmarchelier and Fang, 2016). Thus, we examine the moderating role of each cultural dimension separately in our study and report the findings in Table 9.

Table 6, including the six dimensions of culture with other relevant control variables in our empirical model, indicates to a negative relationship with unemployment for the orientation and indulgence dimensions. Table 9 shows there to be a significant effect on unemployment when the six cultural dimensions are used as moderators.

When we include the interaction terms for different cultural dimensions, except individualism, the other five dimensions strengthen the moderating effect. Simply put, the findings in Table 9 indicate that except for individualism, when considering cultural dimensions as moderators, we observed more employment creation instead of destruction, supporting Hypothesis 2. Researchers who consider only certain dimensions to examine technology adoption in a country or who study the effect of several cultural dimensions in one particular country

Table 9
The moderating effect of cultural dimensions.

Moderating effect (centralised)							
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Unemployment	Unemployment	Unemployment	Unemployment	Unemployment	Unemployment	Unemployment
Robotic adoption	−0.516***	−0.475***	−0.319***	−0.551***	−0.330***	−0.249**	−0.632***
	(0.0764)	(−6.20)	(−4.03)	(−7.02)	(−4.22)	(−1.96)	(−6.60)
R&D	−0.000114***	−0.114***	−0.113***	−0.107***	−0.106***	−0.111***	−0.111***
	(9.93e-06)	(−11.44)	(−11.48)	(−10.08)	(−10.50)	(−11.65)	(−10.97)
Education	8.431***	8.629***	8.761***	8.212***	8.307***	8.540***	8.418***
	(0.428)	(19.95)	(19.85)	(18.56)	(20.49)	(19.76)	(19.76)
Average workhr	−4.078***	−3.988***	−3.971***	−4.023***	−3.715***	−4.007***	−4.089***
	(1.316)	(−3.07)	(−3.07)	(−3.08)	(−3.17)	(−3.06)	(−3.13)
Trade	−0.406***	−0.465***	−0.484***	−0.396***	−0.367***	−0.400***	−0.405***
	(0.0982)	(−4.47)	(−4.81)	(−4.02)	(−3.75)	(−4.00)	(−4.12)
Population	0.00662***	0.007***	0.007***	0.006***	0.007***	0.006***	0.007***
	(0.000532)	(12.74)	(12.59)	(11.08)	(13.11)	(11.72)	(12.23)
GDP	3.386***	3.298***	3.004***	3.520***	3.006***	2.967***	3.545***
	(0.297)	(11.03)	(9.89)	(11.34)	(10.40)	(9.29)	(11.32)
Innovation	−0.188***	−0.186***	−0.176***	−0.195***	−0.185***	−0.184***	−0.188***
	(0.0203)	(−9.17)	(−8.46)	(−9.47)	(−9.26)	(−8.94)	(−9.30)
Power distance	0.0744***	0.078***	0.077***	0.071***	0.070***	0.074***	0.073***
	(0.00460)	(14.91)	(16.27)	(13.84)	(15.16)	(15.89)	(15.05)
Individualism	0.0414***	0.046***	0.047***	0.039***	0.043***	0.042***	0.039***
	(0.00698)	(6.40)	(6.80)	(5.17)	(6.11)	(5.93)	(5.39)
Masculinity	0.00526	0.005	0.003	0.007*	0.003	0.005	0.004
	(0.00345)	(1.48)	(0.93)	(1.79)	(0.98)	(1.36)	(1.31)
Uncertainty avoidance	0.0183***	0.018***	0.021***	0.019***	0.021***	0.023***	0.016***
	(0.00384)	(4.76)	(5.32)	(4.82)	(5.44)	(5.37)	(4.04)
Orientation(lto)	−0.0319***	−0.031***	−0.030***	−0.029***	−0.019***	−0.030***	−0.031***
	(0.00624)	(−4.99)	(−4.77)	(−4.29)	(−2.85)	(−4.91)	(−5.01)
Indulgence	−0.0385***	−0.037***	−0.034***	−0.041***	−0.038***	−0.032***	−0.045***
	(0.00671)	(−5.49)	(−4.91)	(−6.11)	(−5.68)	(−4.88)	(−6.27)
Robotic adoption_c * Power distance_c		−0.008**					
		(−2.50)					
Robotic adoption_c * Individualism_c			0.008***				
			(3.80)				
Robotic adoption_c * Masculinity_c				−0.004**			
				(−1.97)			
Robotic adoption_c * Uncertainty avoidance_c					−0.025***		
					(−7.93)		
Robotic adoption_c * Orientation_c						−0.008**	
						(−2.36)	
Robotic adoption_c * Indulgence_c							−0.008*
							(−1.91)
Constant	−37.93***	−38.609***	−37.086***	−38.049***	−36.315***	−35.556***	−38.583***
	(6.175)	(−6.31)	(−6.10)	(−6.20)	(−6.54)	(−5.83)	(−6.26)
Observations	1980	1980	1980	1980	1980	1980	1980
R-squared	0.510	0.510	0.512	0.510	0.520	0.511	0.510

Notes: Pooled OLS with industry and year is used. The dependent variable is unemployment.; Independent variable is Robotic adoption. Control variables are Logarithm of Trade (trade); Logarithm of GDP per capita, current U.S. dollars (GDP); Logarithm of average worked hours (Average workhr); Innovation Index (inn); Population by Country (Population); Logarithm of Tertiary school enrolment (Education); Research and development investment (U.S. trillion dollars) (R&D). The moderator variables (cultural dimensions): Individualism/collectivism (Individualism), Uncertainty avoidance index (Uncertainty avoidance) dimensions, Power distance (PDI), Masculinity/femininity (Masculinity), Long-term/short-term orientation (orientation), Indulgence versus restraint (Indulgence). Multiplicative variables (moderating effects of cultural dimensions) marked with the multiplication sign (×); Centralised variables mark with the sign (_). t-Statistics are based on robust standard errors and shown in parentheses.

*** 1% significance level.

** 5% significance level.

* 10% significance level.

still need to complete their findings (Erumban and De Jong, 2006; Khan, 2022). We visually represent the findings in Figs. 2 and 3. In Fig. 2 (2-5), we find that power distance, masculinity, uncertainty avoidance, orientation and indulgence negatively moderate the relationship between unemployment and robotic adoption, especially when one particular dimension is prominent in a country. In Fig. 3, we find that individualism positively moderates the main effect. The findings are supported by the theoretical framework proposed in this study. It is evident that any innovation diffusion and absorption by a country takes longer, and besides the different economic factors, the dominance of national culture plays an important role.

According to Fig. (2-1) in Fig. 2, the slopes of low and high PDI are close to each other, indicating that the moderating effect of PDI does not significantly differ with changes in the PDI score.[12] This demonstrates that the moderating effect of PDI remains robust at both high and low values. Countries with a high PDI index produce more significant employment creation than countries with a low PDI index under the same manner of robotic adoption. Countries with high PDI are less innovative (Bukowski and Rudnicki, 2019). However, when perceiving the benefits of robotic adoption centralised decision-making tends to facilitate the rapid implementation of robotics, which can have a more significant positive impact on employment.

[12] The intercept term is negative and significant, so the vertical coordinate also shows negative values.

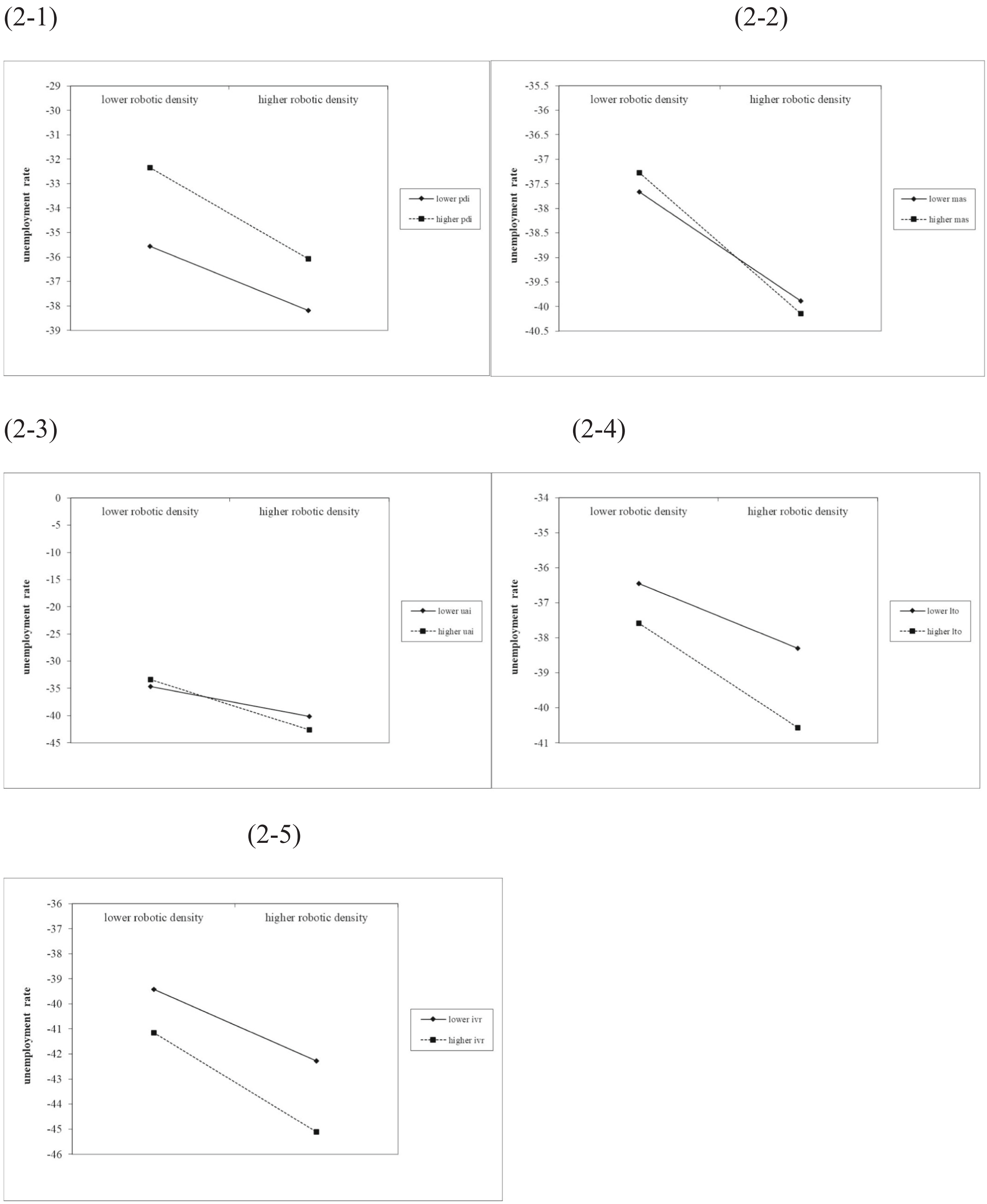

Fig. 2. Moderate effect. Notes: Power distance (PDI), masculinity (MAS), uncertainty avoidance index (UAI) dimensions, orientation (LTO), indulgence versus restraint (IVR), respectively.
Source: Derived by Authors.

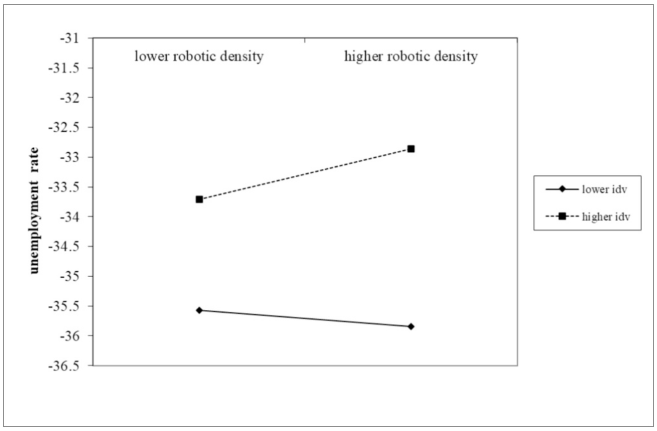

Fig. 3. Moderating effect of IDV. Note: Individualism (IDV).
Source: Derived by authors.

In Fig. (2-2), the slopes of low and high MAS are close to each other, indicating that the moderating effect of MAS does not significantly differ with changes in score. This demonstrates that the moderating effect of MAS remains robust at both high and low values. Countries with a high MAS index produce more significant employment creation than countries with a low MAS index under the same robotic adoption. In countries with a high masculinity index, people pursue material wealth, value social status, and have a strong sense of competition (Hofstede, 2001). In this circumstance, people are more likely to utilise robotics to enhance their competitiveness and maximise productivity gains from robots. Therefore, the employment effect of robotic adoption is also strengthened. Accordingly, countries with high masculinity may be more resistant to the negative side of robotics adoption, while employment effectiveness could be strengthened.

According to Fig. (2-3), the slopes of low and high UAI are close to each other, indicating that the moderating effect of UAI does not significantly differ with changes in UAI score. This demonstrates that the moderating effect of UAI remains robust at both high and low values. The reason for this could be that countries with high UAI scores have been more cautious in adopting robotics, paying more attention to the potential job destruction associated with robotics adoption and deliberately avoiding the risks.

According to Fig. (2-4), the slopes of low and high LTO are close to each other, indicating that the moderating effect of LTO does not significantly differ with changes in the LTO score. This demonstrates that the moderating effect of LTO remains robust in both high and low values. Countries with a high degree of long-term orientation have a social preference for a more pragmatic approach. They encourage thrift and endeavour to embrace modern technology to prepare for the future. That is, countries with a forward-looking perspective are more likely to be effective when responding to robot adoption, and the employment effect is promoted.

According to Fig. (2-5), the slopes of low and high IVR are close to each other, indicating that the moderating effect of IVR does not significantly differ with changes in the IVR score. This demonstrates that the moderating effect of IVR remains robust at both high and low values.

Cultures leaning toward restraint often view life as challenging, emphasising duty and moral discipline over freedom. Conversely, indulgent cultures are marked by optimism, a sense of personal control, impulsiveness, and the value placed on friendships and freedom of speech. A more indulgent society reduces the restrictions on the adoption of technology, thus enhancing the employment effects of robots.

The slopes of low and high IDV significantly differ with changes in the IDV score. This demonstrates that the total moderating effect of IDV is significantly negative. When we divide the groups into low IDV scores, the moderating effect remains negative; however, it persists when focusing on the high IDV score group.

Individualistic cultures encourage competition and personal achievement, which may foster incentives for technological innovation and robotic adoption (Griffith and Rubera, 2014). Collectivism may promote innovation by promoting nationwide efforts to develop innovative solutions to national challenges (Taylor and Wilson, 2012).

In Table 10, we quantify and analyse the marginal effect of six interaction terms.

We examine whether PDI moderates the relationship between robotic adoption and recorded unemployment. The interaction term is negative and statistically significant ($\beta = -0.008$, $p < 0.05$), indicating that the association between robotic adoption and unemployment varies by cultural context. To quantify the magnitude of this moderation, we report the average marginal effects of robotic adoption evaluated at representative PDI values. At a low level of PDI (P25 $\approx$ 40), a one-unit increase in robotic adoption is associated with a 0.349 percentage-point reduction in unemployment (SE = 0.094; 95% CI [−0.534, −0.164]). At a high level of PDI (P75 $\approx$ 68), the corresponding reduction is 0.605 percentage points (SE = 0.090; 95% CI [−0.782, −0.429]). The contrast between high and low PDI is ΔAME = −0.256 percentage points (95% CI [−0.457, −0.055]; $p = 0.012$), implying that a higher power distance amplifies the unemployment reduction of robotic adoption.

The interaction term of IDV is positive and statistically significant ($\beta = 0.008$, $p < 0.01$), indicating that the association between robotic adoption and unemployment varies by IDV context. At a low level of IDV (P25 $\approx$ 33), a one-unit increase in robotic adoption is associated with a 0.441 percentage-point reduction in unemployment (SE = 0.078; 95% CI [−0.593, −0.288]). At a high level of IDV (P75 $\approx$ 71), the corresponding reduction is 0.194 percentage points (SE = 0.093; 95% CI [−0.376, −0.011]). The contrast between high and low IDV is ΔAME = +0.247 percentage points (95% CI [0.120, 0.375]; $p = 0.038$), implying that higher individualism attenuates the unemployment reduction effect.

The interaction term of MAS is negative and statistically significant ($\beta = -0.0038, p < 0.05$), indicating that the association between robotic adoption and unemployment varies by cultural context. At a low level of MAS (P25 $\approx$ 31), a one-unit increase in robotic adoption is associated with a 0.491 percentage-point reduction in unemployment (SE = 0.075; 95% CI [−0.638, −0.343]).At a high level of MAS (P75 $\approx$ 66), the corresponding reduction is 0.614 percentage points (SE = 0.093; 95% CI [−0.796, −0.431]). The contrast between high and low MAS is ΔAME = −0.123 percentage points (95% CI [−0.245, −0.0004]; $p = 0.049$), implying that higher masculinity amplifies the unemployment reduction effect.

The interaction term of UAI is negative and statistically significant ($\beta = -0.025$, $p < 0.001$), indicating that the association between robotic adoption and unemployment varies by cultural context. At a low level of UAI (P25 $\approx$ 60), a one-unit increase in robotic adoption is associated with a 0.064 percentage-point change in unemployment (SE = 0.091; 95% CI [−0.114, 0.242]), which is not statistically distinguishable from zero. At a high level of UAI (P75 $\approx$ 86), the corresponding reduction is 0.738 percentage points (SE = 0.096; 95% CI [−0.926, −0.551]). The contrast between high and low UAI is ΔAME = −0.803 percentage points (95% CI [−1.001, −0.604]; $p < 0.001$), implying that higher uncertainty avoidance amplifies the reduction of unemployment. The moderation is primarily driven by the negative effect at high UAI rather than the significant effect at low UAI.

The interaction term of LTO is negative and statistically significant ($\beta = -0.008$, $p < 0.05$), indicating that the association between robotic adoption and unemployment varies by culture. At a low level of LTO (P25 $\approx$ 44), a one-unit increase in robotic adoption is associated with a 0.123 percentage-point reduction in unemployment (SE = 0.171; 95% CI [−0.459, 0.213]), which is not significant. At a high level of LTO (P75 $\approx$ 69), the corresponding reduction is 0.379 percentage points (SE = 0.092; 95% CI [−0.560, −0.199]). The contrast between high and low LTO is ΔAME = −0.256 percentage points (95% CI [−0.470, −0.044]; p

Table 10
Average marginal effects (AME) of robot adoption on recorded unemployment at representative culture values, and contrasts (ΔAME: P75 − P25).

Cultural dimension	Level	AME (pp per + 1 robotic)	SE	95% CI	*p*-Value	ΔAME (P75–P25)	95% CI	p-Value
Power distance	P25	−0.349	0.094	[−0.534, −0.164]	0.000	**−0.256**	[−0.457, −0.055]	0.012
	P75	−0.605	0.090	[−0.782, −0.429]	0.000			
Individualism	P25	−0.441	0.078	[−0.593, −0.288]	0.000	**0.247**	[+0.120, +0.375]	0.038
	P75	−0.194	0.093	[−0.376, −0.011]	0.038			
Masculinity	P25	−0.491	0.075	[−0.638, −0.343]	0.000	**−0.123**	[−0.245, −0.0004]	0.049
	P75	−0.614	0.093	[−0.796, −0.431]	0.000			
Uncertainty avoidance	P25	0.064	0.091	[−0.114, +0.242]	0.479	**−0.803**	[−1.001, −0.604]	0.000
	P75	−0.738	0.096	[−0.926, −0.551]	0.000			
Long-term orientation	P25	−0.123	0.171	[−0.459, +0.213]	0.472	**−0.256**	[−0.470, −0.044]	0.018
	P75	−0.379	0.092	[−0.560, −0.199]	0.000			
Indulgence	P25	−0.509	0.074	[−0.654, −0.364]	0.000	**−0.25**	[−0.507,+0.007]	0.056
	P75	−0.759	0.147	[−1.048, −0.470]	0.000			

Note. Outcome: AME = change in unemployment in percentage points per +1 unit of robotic adoption. Robot adoption and culture variables; “P25/P75” denote the 25th/75th percentiles of the culture dimension. All models include industry and year fixed effects and the full set of controls (R&D, education, average working hours, trade openness, population, GDP per capita, innovation). Robust (heteroskedasticity-consistent) standard errors reported; two-sided *p*-values. $N = 1980$. Confidence intervals in brackets.

= 0.018), implying that higher long-term orientation amplifies the unemployment reduction effect of robotic adoption. This moderation is primarily driven by the significant effect at high LTO rather than low LTO.

The interaction term of IVR is negative and insignificant at conventional thresholds ($\beta = -0.008$, $p < 0.1$), indicating that the evidence for moderation is borderline. At a low level of IVR (P25 ≈ 29), a one-unit increase in robotic adoption is associated with a 0.509 percentage-point reduction in unemployment (SE = 0.074; 95% CI [−0.654, −0.364]). At a high level of IVR (P75 ≈ 62), the corresponding reduction is 0.759 percentage points (SE = 0.147; 95% CI [−1.048, −0.470]). The contrast between high and low IVR is ΔAME = −0.250 percentage points (95% CI [−0.507, 0.007]; $p = 0.056$), implying that higher indulgence may amplify the unemployment reduction effect of robotic adoption, but the evidence is borderline.

In addition, to check the robustness of the findings, we conduct an alternative test and trimmed the overall sample. We removed Japan and South Korea from the sample as these countries have the highest robotic densities in the total sample. In Table 11, when we rerun the regression, the findings remained significant and supported the initial results reported in Table 6 and 9.

Table 11
Robustness checks.

Variables	(1)	(2)	(3)
	Unemployment	Unemployment	Unemployment
Robotic adoption	−0.544***	−0.316***	−0.541***
	(−6.86)*	(−4.05)	(−5.67)
R&D		−0.059***	−0.095***
		(−7.73)	(−9.84)
Education		7.975***	8.760***
		(20.07)	(20.20)
Average workhr		−4.925***	−3.691***
		(−3.03)	(−2.94)
Trade		−0.349***	−0.238**
		(−3.76)	(−2.45)
Population		0.005***	0.005***
		(10.01)	(9.43)
lngdp		2.472***	3.219***
		(7.48)	(10.25)
Innovation		−0.273***	−0.165***
		(−13.70)	(−7.82)
Power distance			0.069***
			(13.07)
Individualism			0.019**
			(2.37)
Masculinity			0.009**
			(2.17)
Uncertainty avoidance			0.021***
			(5.40)
Orientation(lto)			−0.013**
			(−2.13)
Indulgence			−0.035***
			(−5.34)
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Constant	10.026***	−16.019**	−40.568***
	(24.86)	(−2.27)	(−6.81)
	−0.544***	−0.316***	−0.541***
Observations	1860	1860	1860
R-squared	0.087	0.425	0.499

Notes: Pooled OLS with industry and year is used. The dependent variable is unemployment; Independent variable is Robotic adoption. Control variables are Logarithm of Trade (trade); Logarithm of GDP per capita, current U.S. dollars (GDP); Logarithm of average worked hours (Average workhr); Innovation Index (inn); Population by Country (Population); Logarithm of Tertiary school enrolment (Education); Research and development investment (U.S. trillion dollars) (R&D). The moderator variables (cultural dimensions): Individualism/collectivism (Individualism), Uncertainty avoidance index (Uncertainty avoidance) dimensions, Power distance (PDI), Masculinity/femininity (Masculinity), Long-term/short-term orientation (orientation), Indulgence versus restraint (Indulgence). t-statistics are based on robust standard errors and shown in parentheses.
*** 1% significance level.
** 5% significance level.
* 10% significance level.

5. Discussion and conclusion

In this study, we examined the impact of robotics adoption on unemployment across a sample of countries by introducing the moderating effect of the national culture.

5.1. Academic contribution

Cultural dimensions are widely used in research related to technological innovation and adoption (De Mooij, 2000; Jung and Lim, 2020). However, robotics has not received sufficient scholarly attention concerning the latest technological advancements (Khan, 2022). Thus, in this study, we critically examine the impact of robotics adoption on unemployment in different countries, considering the cultural beliefs and practices of said countries. We find there to be a significant negative relationship between robotics adoption and unemployment in our sample countries, which clearly contributes to the discussion in the literature on the topic (Dekle, 2020; Gentili et al., 2020). We find variation across countries when we consider the cultural dimensions as part of explaining this relationship. The findings of our study support the literature on the importance of cultural dimensions in the discussion of technology adoption (Erumban and De Jong, 2006).

In addition to this contribution to the literature, the adoption of the theoretical framework to explain the research question is unique to this study. Typically, either innovation diffusion theory or absorption capacity theory is used in technology adoption by individuals or organisations (Cohen and Levinthal, 1989; Kim and Chakraborty, 2024). In the existing literature on the impact of robotics on employment, there is an unresolved tension. To frame this complexity theoretically, we integrate Innovation Diffusion Theory and Absorptive Capacity Theory. This dual-theoretical lens allows us to interrogate not only how robotics adoption spreads but also how different national systems absorb and benefit from such adoption. In doing so, we contribute a more comprehensive understanding of the cross-national variation in employment outcomes an area that recent scholarship (e.g., Dabić et al., 2023; Castellacci and Natera, 2013) identifies as requiring further empirical attention. Furthermore, we demonstrate that considering cultural and traditional macroeconomic factors provides a more comprehensive understanding of technology adoption. When dealing with new technology, different cultures accept the technology at varying paces, which is determined by the way the knowledge is diffused across countries.

5.2. Practical implications

The findings of this research provide important insights for both policymakers and scholars concerned with the relationship between robotics adoption and employment. Our results consistently demonstrate that, across a range of cultural contexts, the creative employment effects of robotics adoption outweigh the displacement effects. However, the degree and nature of this impact is not uniform. Cultural factors such as uncertainty avoidance, long-term orientation, and societal attitudes toward innovation significantly moderate the adoption process and its employment consequences. These findings reinforce the need to consider culture not as a peripheral variable, but as a key factor that shapes the national readiness for technological transformation.

From a policy perspective, this suggests that uniform approaches to robotics adoption are unlikely to be effective. National strategies must be tailored to local institutional capabilities and cultural norms. Countries with low robot adoption and limited innovation infrastructure should prioritise investments in absorptive capacity through education, vocational training, research and development, and digital infrastructure. Such countries may also benefit from structured international collaboration with early adopters like Japan and Germany, who can share technological expertise and implementation models that mitigate risks and lower adoption barriers. Additionally, lower-income countries facing funding constraints can still achieve returns by strategically allocating resources to high-impact, context-appropriate robotics investments.

In high-adoption economies, the policy agenda should shift toward maintaining momentum while ensuring equitable outcomes. This includes promoting inclusive upskilling programs, adapting social protection systems to support displaced workers, and encouraging innovation ecosystems that reinforce employment creation. Governments should also consider fostering bilateral or multilateral platforms to share best practices and support global convergence in robotics readiness.

These insights contribute to the theoretical debates by illustrating how national culture acts as a moderating force in the diffusion and impact of robotics technology. Integrating cultural variables into frameworks such as Innovation Diffusion Theory and Absorptive Capacity Theory enhances their explanatory power and pushes the literature toward more context-sensitive understandings of technological change. Our findings challenge the assumptions of cultural neutrality in automation outcomes and provide a foundation for future comparative research on how societies negotiate technological disruption.

In sum, effective policy design must reflect the nuanced interplay between technological potential and cultural readiness. Embracing this complexity can enable more inclusive, adaptive, and sustainable approaches to robotics adoption worldwide. Thus, our study contributes not only to the theoretical debates on technology and employment but also offers a culturally informed policy blueprint for inclusive and adaptive robotics adoption.

5.3. Limitation and future research

Like other research, our study has limitations. Individual and firm-level robotics adoption data along with other unit-level information would enrich the existing findings. In-depth country-level robotics adoption information related to international trade would provide additional insights for professionals. Our evidence pertains to a balanced panel of 33 countries and six industries over 2010–2019. External validity is therefore bounded by the set of countries with comparable robotic and labour-market statistics in this period. Although our findings reflect the variation in robotic adoption between these countries, the available data doesn't allow us to capture the variation in occupations. Future research can utilise three-dimensional data consisting of country, industry and occupation to investigate how robotics adoption affects the labour market across different industries and occupations within and across the sampled countries. Additionally, due to the controversial reliability of data collection during COVID-19, this study limited the sample to 2019 to ensure the accuracy of the analyses. Future studies could consider the influence of COVID-19 on the adoption of robotic when the data is available. Although Hofstede does not predict global citizens living in multiple cultures, Hofstede's framework is one of the most widely accepted frameworks for investigating national variations across countries in the social sciences (Salehan et al., 2018; Abbasi et al., 2021). Accordingly, we adopt it in this research.

CRediT authorship contribution statement

Guangjie Du: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Suman Lodh:** Writing – original draft, Visualization, Validation. **Monomita Nandy:** Writing – review & editing, Writing – original draft, Conceptualization. **Marina Dabić:** Writing – review & editing, Writing – original draft, Supervision. **Vikas Kumar:** Writing – review & editing, Writing – original draft, Validation. **Jyoti Choudrie:** Writing – review & editing, Writing – original draft, Validation.

Ethics statement

Not applicable.

Declaration of competing interest

None.

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Appendix 1

Variable	Definition	Data source	Literature reference
Dependent variable			
Unemployment	The share of the labour force without work but available for and actively seeking employment	World Bank	(Aghion et al., 2016, p. 3881; Jung and Lim, 2020)
Independent variable			
Robotic adoption	The total stock of robotics divided by the number of employed people per thousand	IFR	(Klenert et al., 2022, p. 285)
Control variable			
Research and development (R&D)	Country investment in research and development measured in US trillion dollars	World Bank	(Koch et al., 2021)
Education	Logarithm of tertiary school enrolment (percent of all eligible children)	UNESCO	(Castellacci and Natera, 2013)
Average work hour	Logarithm of average worked hours	ILO	(Desmarchelier and Fang, 2016)
Net trade (trade)	Logarithm of Net Trade.Net trade in goods and services is derived by offsetting imports of goods and services against exports of goods and services. Exports and imports of goods and services comprise all transactions involving a change of ownership of goods and services between residents of one country and the rest of the world. Data are in current U.S. dollars.	World Bank	(Castellacci and Natera, 2013)
Population	Population by country	UN	(Fu et al., 2021)
GDP	Logarithm of GDP per capita, current U.S. dollars. GDP per capita is gross domestic product divided by midyear population. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Data are in current U. S. dollars.	World Bank	
Innovation	The Global Innovation Index includes two sub-indices: the Innovation Input Sub-Index and the Innovation Output Sub-Index. The first sub-index is based on five pillars: Institutions, Human capital and research, Infrastructure, Market sophistication, and Business sophistication. The second sub-index is based on two pillars: Knowledge and technology outputs and Creative outputs. Each pillar is divided into sub-pillars and each sub-pillar is composed of individual indicators.	WIPO	(Castellacci and Natera, 2013)
Cultural dimension			
Power distance Individualism Masculinity Uncertainty avoidance Orientation(lto) Indulgence	Refer to Table 1	Hofstede, 1984, 2001; Hofstede et al., 2010, 2010)	(Abbasi et al., 2021; Desmarchelier and Fang, 2016; Khan, 2022)
Moderators			
Power distance (Robotic adoption_c * Power distance_c)	Interaction terms for robot adoption and power distance	IFR and Hofstede et al. (2010)	(Malik et al., 2021; Strese et al., 2016; Jadil et al., 2022)
Individualism (Robotic adoption_c * Power distance_c)	Interaction terms for robot adoption and individualism		
Masculinity (Robotic adoption_c * Power distance_c)	Interaction terms for robot adoption and masculinity		
Uncertainty avoidance (Robotic adoption_c * Power distance_c)	Interaction terms for robot adoption and uncertainty avoidance		
Orientation(lto) (Robotic adoption_c * Power distance_c)	Interaction terms for robot adoption and Orientation(lto)		
Indulgence (Robotic adoption_c * Power distance_c)	Interaction terms for robot adoption and indulgence		

Appendix 2. Moderating effect of culture dimensions

Culture dimension	High values - expected moderating effect	Low values expected moderating effect
Power distance	+	−
Individualism	−	−/+
Masculinity	+	−
Uncertainty avoidance	+	−
Long-term goal-oriented	+	−
Indulgence	+	−

Note: Derived by author.

Appendix 3. IDT and conflicting employment outcomes

The five stages of Innovation Diffusion Theory (IDT) offer a useful framework for interpreting why robotics adoption leads to conflicting employment outcomes across a range of countries and contexts. The following outline explains how each stage can help unpack this tension:

1. Knowledge

This stage involves exposure to the existence of robotics technology and some understanding of its functions. In countries with strong R&D

ecosystems or access to global innovation channels, early exposure fosters timely awareness and preparation. Others may lag, creating asynchronous adoption timelines that contribute to uneven employment effects globally.

2. Persuasion
   At this point, potential adopters form an attitude toward the technology based on perceived benefits and risks. In high-income nations, where case studies highlight productivity gains and task augmentation, this persuasion is often positive. In contrast, developing economies may anticipate labour displacement without sufficient social safety nets, leading to hesitation or selective adoption, modulating the impact on employment.
3. Decision
   Stakeholders decide whether to adopt or reject the innovation. Some governments and firms may adopt robotics proactively to boost competitiveness, seeing employment gains through complementary roles. Others may delay adoption, resulting in missed productivity benefits or reactive responses that displace rather than reconfigure labour.
4. Implementation
   This is where the technology is put to use, and practical challenges arise. Usually developed economies with a high absorptive capacity can implement robotics in ways that preserve or create jobs. For countries with lower institutional or human capital readiness, implementation may lead to inefficiencies, job losses, or the underutilisation of the technology.
5. Confirmation
   At this stage, stakeholders evaluate the outcomes to reinforce or reconsider their decision. If employment gains are visible, the innovation is embraced and diffused further. If negative outcomes emerge, especially in contexts lacking social or policy buffers, adoption may stall or even reverse.

In summary, these five stages help explain why robotics adoption does not produce uniform outcomes. Countries are situated at different stages of the diffusion process, and the socio-economic context mediates each stage's impact. By mapping empirical inconsistencies onto the IDT framework, we gain insight into why robotics may generate job losses in one context and net gains in another.

Data availability

The authors do not have permission to share data.

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